New Firms in Nanotechnology: Does Experience Improve the Entrepreneur's Revenue Forecast Performance?

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ABSTRACT,

This research is a survey study analyzing the influence of CEO's industry and startup experience on the revenue forecast accuracy for venture capital backed nanotechnology firms. Other determinants like age, sex, and education are also taken into account. Literature already shows evidence that industry experience is associated with forecasting accuracy, especially in high-tech industries. But is this proof also applicable for venture capital backed startups? This research tries to analyze this. By using an unique dataset analysis is done to the influence of experience on the revenue forecast accuracy. Due to a low sample size and due to not meeting the requirements for multiple linear regression analysis, a Pearson chi-square and Fisher's exact test is performed to find dependency between Industry experience, Startup experience, age and revenue forecast accuracy. The results don't show significance for the variables industry experience and age, which means no dependency between the variables. However, the test gave a significant result for startup experience, which means there is dependency between startup experience and revenue forecast accuracy. Because of the low sample size, it is difficult to give fully valid conclusions, hence why future research could go further into this topic using bigger sample sizes and possible a different focus group.

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Startups, Venture Capital, Revenue Forecasting Accuracy, Nanotechnology, Experience

1. INTRODUCTION

1.1 Situation and Complication

In 2018 a total of 255 start-ups/scale-ups received funding through venture capital in the Netherlands, the total fund raised by Dutch start-ups/scale-ups was approximately 750 million Euros which is almost €90 million more than in 2017.

These results from a data analysis of Golden Egg-Check show the impact of venture capital on the start-up community. The total amount of funds raised by start-ups in the Netherlands has more than doubled from 2016 to 2018. As mentioned in a recent study by Davila, Foster & Gupta (2003): "companies receiving venture capital grow faster than their counterparts", this increase in funding also has a big impact on the growth of start-ups.

But what exactly is venture capital? Venture capital often consists of three parts: the General Partners; the Limit Partners; and the portfolio of investments. The Limit Partners raise money together in a Venture Capital Fund, the money of this fund will then be invested in a series of companies (Start-ups) by the General Partners. The goal of these investments is to get a large return on investment, often these returns are made by exiting the firm in the form of an acquisitions or IPO's.

Start-ups seeking financing often turn to venture capital firms to provide capital, but also to assist them strategically, introduce them in their network for potential customers, partners, employees and much more. To obtain venture capital financing, these start-ups have to create a strong investor pitch to attract interest of a VC. When the VC is interested in investing in the start-up, a "term sheet" will be presented to the firm. The "term sheet" is basically a blueprint for the relationship between the investor and the entrepreneur, it states agreements about for example control issues and rights the investors will get. If the entrepreneur succeeds to convince the VC to invest in his or her start-up, the VC can decide to invest in multiple forms.

The complication this study wants to focus on is that "start-ups firms are arguably the most informationally opaque" (Berger and Udell, 1998, p.622), which can make their investor pitch somewhat unreliable. This makes it difficult for the Venture capitalists to make a good assessment of the situation and thus make a good decision whether to invest or not. Especially for Seed funding VC's, where the start-ups generally don't have much historical data, the forecast provided in the investors pitch will be based more on expectations and desired outcomes. Cooper and others (1994) find in their research that Entrepreneurs tend to be overly confident, which can also have a negative impact on the accuracy of the entrepreneurs forecast.

The extent to which this complication of unreliable and inaccurate forecast is occurring might be different for the various industries. To exclude this from this research, this study will focus on just one industry, this in order to be able to draw a more valid and reliable conclusion. The industry of focus is the Nanotechnology industry, this because it is a fast-growing market with increasing investor interest. According to the Global Nanotechnology Market Outlook 2024, the compounded annual growth rate of the Nanotechnology industry is around 16.5% between 2018 and 2025. This growth in market size will thus be an increase from 7.24 billion dollars in 2017 to 24.56 billion dollars by 2025. Because Nanotechnology is such a fast growing industry, the interest of investors in nanotechnology is also growing.

1.2 Research Question

This research aims to give more insights about the accuracy of the expectations/forecast made in the investor pitch and whether the CEO's experience has influence on this accuracy. Because these investor pitches contain expectations concerning different values, this research focusses on the accuracy of the revenue forecast. My research question will be: *To what extent does the entrepreneurs experience influence the accuracy of revenue forecast made by venture capital backed nanotech Startups?* The goal is to research the influence of the CEO's experience on revenue forecast accuracy, focusing on venture capital backed Nanotech Startups. The CEO is chosen because he or she is responsible for decisions made, and because he or she is involved in most early stage activity. The CEO experience will be divided into two parts: Industry Experience and Start-Up Experience. Industry Experience is the extend of years to which the entrepreneur already has experience in the Nanotechnology industry. Start-up Experience is the amount of times an entrepreneur already started a business before their current one.

2. LITERATURE

2.1 Background

To get more knowledge about this subject a structured literature review was performed using Boolean search terms on Scopus.

Lorenz and Homburg (2018) found in their research that both forecast's characteristics as well as analyst's characteristics are determinants of revenue forecast accuracy made by financial analysts. These characteristics contain "Forecast horizon, days elapsed since the last forecast, analysts' forecasting experience, forecast frequency, forecast portfolio, reputation, earning forecast issuance, forecast boldness, and analysts' prior performance in forecasting revenues and earnings." (Lorenz and Homburg, 2018, p. 389)

Other researchers also give empirical evidence for a positive correlation between analyst characteristics and forecast accuracy. These characteristics include resources available to analysts, analyst experience and complexity of portfolio covered by analysts (Clement, 1999; Clement and Tse, 2003; Clement and Tse, 2005; Mikhail et al., 1997). Kim, Lobo and Song (2011) re-examined these finding and controlled them for timing advantages They found that firm specific and general experience, previous forecast accuracy, employment at larger brokerage firms, and following fewer industries and companies are negatively related to relative forecast errors.

Another important aspect in forecasting accuracy is the forecaster's overconfidence. As mentioned in a recent study by Invernizzi et al. (2017) overconfidence is linked to overoptimistic forecasts, non-optimal outcomes and thus also to firm failure. As a recent study states: "Overconfidence as proxied by the tendency to make extreme forecasts leads to poor performance." (Deaves, R., Lei, J., Schröder, M., 2019, p. 18). Because working experience is accompanied by less overconfidence (Gloede, O., Menkhoff, L., 2014), it is indirectly also accompanied with better forecasting performance.

2.2 Industry and Startup Experience

Many researchers argue that experience improves the financial forecasting performance. Cassar (2014) goes further than this by dividing experience into Industry experience and Startup experience. He divided these two because forecasting requires both knowledge from the industry (Industry experience) as well as knowledge of possible unexpected challenges related to starting a new firm (Startup experience). Cassar operationalizes industry experience as the number of years the entrepreneur worked in the industry he now started a business in and startup experience as the number of new firms started before their current one. His dependent variable was entrepreneurial forecast performance and he obtained this via the Kaufman Firm Survey. In this survey entrepreneurs were asked how much they thought they met their expectations made when they started the business, possible answers were: 1) did not meet; 2) met; 3) exceeded their expectations.

2.2.1 Industry experience

Forecasting is a task with much variation and heterogeneity which, according to some researchers, makes it too complicated to use knowledge gained from experience for better forecasting performance (Bonner and Lewis, 1990; Clement et al., 2007; Jacob et al., 1999). Although this sounds reasonable, later research shows otherwise. Experience in a certain industry is important because: 1) it increases the possibility to obtain relevant and precise information about the industry of the new business (Landier and Thesmar, 2009; 2) it increases the knowledge about cost structure, pricing, profitability of various market segments and the value chain (Dimov, 2010); 3) it reduces uncertainty of business evaluation because knowledge can be gained about the new business opportunity.

Besides this, Cassar already found empirical evidence that Industry Experience has a significant positive influence on an entrepreneur's forecasting ability (Cassar, 2014). His results show that entrepreneurs with greater industry experience have more realistic expectations/forecasts than those without industry experience. Therefore, I posit the following hypothesis:

Hypothesis 1: Industry experience has a positive association with revenue forecasting accuracy for venture capital backed nanotechnology startups.

2.2.2 Startup Experience

Cassar (2014) did not find significant evidence for an association between Start-up Experience and entrepreneur forecast performance. Besides this, Carmerer and lovallo (1999) and Wright (2001) argue that that forecasting often has a lack of task repetition which makes it impossible to be able to learn by doing. Later research rejects this by concluding that entrepreneurs can gain knowledge about the uncertainty related to starting a business through learning by experimenting (Delmar and Shane, 2006). Although cognitive biases can have a negative effect on effective learning by doing for forecasting (Cassar and Craig, 2009; Hogarth, 1987; Kahneman et al., 1982; Sexton et al., 1997), Corbet (2005) still finds evidence that entrepreneurial judgement and evaluation are improved from learning by doing. Startup experience can even reduce the influence of cognitive biases on the forecast. If the entrepreneur has experience with errors in his/her judgement, he or she will be more aware of the inaccuracy of his/her knowledge and thus possibly act differently (Forbes, 2005). Therefore I posit the following hypothesis:

Hypothesis 2: Startup experience has a positive association with revenue forecasting accuracy.

2.3 Control variables

Besides the literature discussed in the previous sections there are also researchers arguing other determinants than experience to be of importance for overconfidence and thus for forecasting performance. These other determinants are age, education and sex.

The literature (Arabsheibani et al., 2000; Forbes, 2005) Shows us that age is related with overconfidence and thus also with inaccurate forecasting. Forbes (2005) states that older people tend to be more overconfident because they feel more skilled because of their experience. I also suggest age has a positive association with experience and should thus also increase forecasting accuracy. This creates a contradiction which can hopefully be clarified with the data analysis.

The second variable is educational background. Landier and Thesmar (2009) show in their paper that educational background has a positive association with forecasting bias. "Education seems to be positively correlated with high expectations when compared to realizations" (Landier and Thesmar, 2009, p. 142).

The last control variable is sex. "Psychological research has established that men are more prone to overconfidence than women, particularly so in male dominated realms such as finance." (Barber and Odean, 1998, p. 26) Other literature also shows that overestimating future performance is higher with men than with women (Puri and Robinson, 2007; Ucbasaran et al., 2010).

2.4 Conceptual Framework

Literature shows that both industry experience as well as startup experience have a positive influence on (financial) forecast accuracy. By reviewing the literature and applying it to the situation stated in the introduction, and by controlling for the control variables discussed in the chapter before the following Conceptual framework came forward:

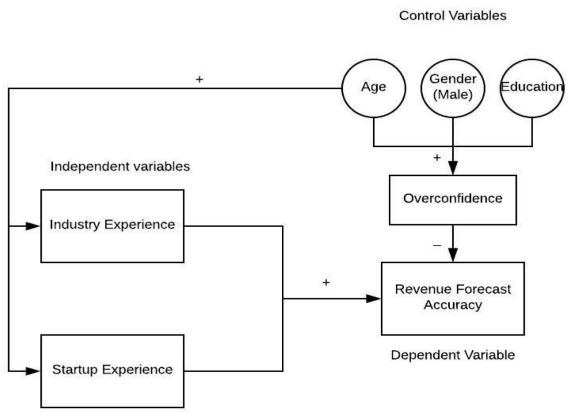

Figure 1: Conceptual Framework

The hypothesis is that both industry and/or startup experience has a positive influence on the revenue forecast accuracy for venture capital backed nanotechnology startups. The literature suggests that the control variable all increase overconfidence and thus decreases forecast accuracy. As mentioned in the chapter before I suggest that age is also positively associated with experience and thus indirectly with forecast accuracy which creates a contradiction that needs further research to be clarified. In the next chapter is explained how the conceptual framework will be tested

3. METHODS

3.1 Sample

The population used for this research are the Nanotechnology organizations participating in the NanoNext project. A total of 22 out of 40 participants of the Nanonext project responded and will be the sample of this research. The Units of analysis are venture capital backed Nanotechnology firms, the independent variables are entrepreneur's industrial experience in years and startup experience in number of new firms started. The Dependent variable is the accuracy of the revenue forecast (in %).

The possibility was given to me to make use of a unique dataset in which information was given about the sample. This dataset is created around 2015, and the information is divided into: Pitch; Check; Funding; Team; Lean Canvas; Product; Mark; Financial; Timeline; and Financial valuation.

The Pitch: In the Pitch the participants give a small introduction to their ideas, sometimes a video of an Elevator pitch and/or product explanation is added.

Funding: Funding gives insight about the general information of the proposition (Country / City / Start Date / Category), a funding summary (Funding state / Market Focus / Current Yearly Revenue / Wanted Investment Size / Detail), and Relevant investors.

Team: Team gives insight about the experience and tasks of all the team members and is divided in three parts: 1) Summary: a small introduction about the people involved with the project. 2) Experience: Information is given about the experience of all the team members. 3) Organization: Information is given about the position of the team members within the organizations and the tasks related to these.

Lean Canvas: The organizations first summarize their lean canvas. They also give more in dept information about the problem, their solution for the problem, their unique value proposition, their advantageous, and their customer segments.

Product: For product, the participants give more in depth information about their product / product ideas. They first give a small summary, after this more information is given about the product's characteristics, their Intellectual Property Strategy for the product, and the risks related to the product.

Market: For Market, the participants give more in depth information about the market they want to enter. They first give a small summary, after this more information is give about the market's characteristics, their customers, their competitors, and their value chain

Financial: If applicable, the participants give insight about their current revenue streams and cost structure. Besides this they give a detailed forecast of their customers, revenue, and costs per year (for 5 years). Also the liquidity for each month of the first year will be given and more information is given about further investment needed in a future state.

Timeline: A timeline is shown to give an overview of all the important occurrences which are made in the forecasts

Financial Valuation: A tool is developed by Golden Egg Check to have an easy and quick way of checking the value of a business case.

3.2 Operationalization

3.2.1 Independent variables

3.2.1.1 Industry Experience

Industry experience is the experience a person has withing a certain field. The CEO's participating in the NanoNext project were asked the number of years of working experience they had with nanotechnology. For this, the years working on a Phd within the nanotechnology is also included because it can also give them relevant experiences of possible complications within the Nanotechnology. An average of 12.5 years of working experience in nanotechnology was found in this sample.

3.2.1.2 Startup Experience

Startup experience is experience gained from starting a new firm. CEO's participating in the NanoNext project were asked the number of new businesses they started before their current business. Only 32% of the participants has started one business before their current one, the other 68% did not start a business before.

3.2.2 Dependent variable

The dependent variable is the extent to which the organization met or exceeded their third year revenue expectation in percentages.

Because organizations are often secretive about their current financial data, the difference between actual revenue and forecasted revenue will be asked in percentages instead of the actual revenue in euros. This in combination with the anonymity of the survey is hopefully encouraging entrepreneurs to give honest answers. With asking for a percentual difference instead of actual revenue, I also try to avoid biases arising from the fact that some organizations (often poor performing organizations) do not want to give explicit numbers of their actual revenue.

The average of the extent to which the organization met their expected revenue is 37%. The participant with the most years of industry experience also has also made the most accurate revenue forecast. Further analysis will be performed in order to find significant evidence for dependency between the dependent variables and the independent variable

3.3 Methods of Analysis

3.3.1 Data collection

Both primary data as well as secondary data is used in this research in order to create a useful dataset. Secondary data was collected by doing literature research and using the Nanonext dataset and primary data was collected by performing a survey with participants of the Nanonext project.

3.3.1.1 Primary data

In this research primary data will be collected by performing a small survey at venture capital backed organizations that participated in the NanoNext project. Because asking private information, such as current revenue, might cause difficulties in collecting data, the entrepreneurs will be asked to give the extent to which they met or exceeded their expected revenue (in %). The NanoNext dataset does provide some information about the CEO's experience, but not as specific as required for this research. Hence why questions are also added to collect data about the number of businesses created before their current business and about the number of years of working experience they have in the nanotechnology.

To get a sample size as high as possible I collaborated with my colleague Bas Kippers in conducting a survey. First an attempt was made to call the CEO's, so we could introduce ourselves and give a short explanation about our research. When the CEO's are interested in contributing to the research, an e-mail was send to them with further explanation and with a referral to our online survey. Every organization also received a correspondence number in the mail which they have to use when filling in the survey. This to create an anonymous dataset, but also for us to be able to see which organizations did not answer the survey. Follow-up calls were made when organizations did fill in the survey within a week to ask what caused them to not answer yet. Most CEO's that did not answer at first answered that this was because off a lack of time, but most participants found time to fill in the survey after the follow-up call.

The following questions are asked in the survey:

- What is your correspondence number?
- What is your age?
- How many years work experience do you have with Nanotechnology?
- Did you start any other firms before your current business? If yes, How many?
- What was the actual time-to-market of your product in years?
- To what extent did you reach your expected revenue of the third year made in the investor pitch? (in %)

The fifth question is not related to this research but to a similar research of my colleague Bas Kippers. Thus the first four and the last question will be used to collect the needed data additional to the secondary data available

3.3.1.2 Secondary data

I will be using secondary data provided by Golden Egg Check to get the start-ups revenue forecast data and contact details of these organizations which will help me for my primary data collection. These revenue forecasts are made in 2015 and only the forecasts of the year 2018 (or 2017 if this is their third year) will be used. Because the dataset did not contain the relevant information about the entrepreneur's experience needed for this research, it could not be used. Hence why questions are created in the survey to receive the information needed for the data analysis.

Besides this a structured literature review was performed via Scopus. By using Boolean search terms a specific search was performed on the influence of experience on forecasting performance and overconfidence within forecasting. By checking the titles and abstracts of the results from these search terms, the papers were selected on relevance.

The first search focusing on forecasting performance resulted in 56 papers related to the keywords used and were checked for their relevance. This resulted in 6 relevant papers all suggesting experience improves financial forecast accuracy in their own context (Appendix J)

The second search focusing on overconfidence resulted in 170 papers related to the keywords (appendix I) used and were checked for their relevance. This resulted in only 5 relevant papers. Showing working experience lowers overconfidence, showing overconfidence decreases forecasting performance which can lead to firm failure or excess market entries, but also a paper showing hazard ratio for overconfident entrepreneurs to be lower than their counterparts.

I also made use of the snowball method in which I looked more in dept into the referenced papers especially from the paper "Industry and start-up experience on entrepreneur forecast performance in new firms." (Cassar, 2014). This led to papers supporting but also papers opposing his theory.

3.3.2 Data Analysis

For this research a cross-sectional explanatory research will be performed, in which the Units of analysis are venture capital backed firms, the independent variables are the entrepreneur's industry experience and startup experience, and the Dependent variable is the accuracy of the revenue forecast (in %). SPSS will be the program used for the data analysis and for finding an association between the independent variables and the dependent variable.

In this research a causal relationship between experience and accuracy of revenue forecast is researched, hence the following three aspects of causality have to be taken into account:

1. Time order; X precedes Y in time
2. Association/correlation; X and Y are correlated
3. Non spuriousness; there is no other (third) variable accounting for the correlation

It is clear that the experience of an entrepreneur precedes the financial forecast made in the investor pitch, so an assumption can be made that the time order is right. For the association and Non spuriousness this is not the case. By performing a data analysis via SPSS an association can possibly be proven or invalidated. By making use of different control variables, which the literature has showed us to have influence on the variables, an attempt is made to contain all necessary possible third variables and thus create non spuriousness.

Because the data requires a cross-sectional analysis with two independent variables the intention was to perform a multiple linear regression analysis. When performing multiple linear regression, the dataset should meet some requirements: 1) There must be a linear relationship between the dependent and the independent variables; 2) Multivariate Normality; 3) No Multicollinearity; 4) Homoscedasticity (Bock, De Veaux, & Velleman, 2016). First the linearity between the dependent and independent variables can be tested using scatterplots. Multivariate Normality states that the residuals of the variables should be equally distributed, this can be tested using Q-Q plots in SPSS. By using Variance Inflation Factor values a test can be done whether the independent variables are not highly correlated with each other. By making a scatterplot of residuals versus predicted values a check can be done for homoscedasticity. The data is homoscedastic when there is no clear pattern in the distribution. As shown in the next chapter, the results show that multiple requirements are not met.

To avoid a type II error (acceptance of a false hypothesis), the university of Dusseldorf created a software in order to determine a desired sample size. This software takes multiple values into account including the alpha, the power, and the effect size. According to Howell (2010) a generally accepted power is 0.80 and it is common to use an alpha of 0.5. It is also advised by Statistical Solutions to use a medium effect in the sample size calculation (f^2 = 0,15). Using the software and the most commonly used alpha, power and effect size, Statistics Solutions gives a desired sample size of 68. This combined with the data not meeting all requirements for multiple linear regression analysis, would make the results of multiple linear regression analysis invalid. Hence why a Pierson chi-square and Fisher 's exact test is performed.

4. RESULTS

First, to check for potential outliers and anomalies in our dataset a histograms are computed (Appendix A). Both industry experience as well as age seem somewhat normally distributed, revenue forecast accuracy has some skewness but no normal distribution. With startup experience 15 out of 22 participants have 0 new firms started before and the other 7 had 1. For the control variables sex and education almost no variation was present (21 men, 22 Phd). Because 21 out of 22 participants are men, and because 22 out of 22 participants have education level 4 (Phd), these results will not be taken into account for the further research.

Secondly, test are performed to check whether the dataset meets the requirements for performing a multiple linear regression analysis. First scatterplots are created in order to determine whether linearity is present between the dependent and the independent variables (Appendix B). It seems that no linearity can be found between the independent variables and dependent variable, thus the requirement is not met. When creating Q-Q plots (Appendix D), it seems that industry experience and revenue forecast experience have a decent fit with the normal curve, thus being somewhat normally distributed. But Industry experience is not fitting the line, meaning no normal distribution, thus the Multivariate Normality requirement is also not met. As shown in the appendix (Appendix E), the no multicollinearity requirement is met. There not just one clear rule that states which VIF value means multicollinearity, but a value of 1 is no multicollinearity and the higher the value the higher the correlation. With a VIF value of 1.034, it is valid to conclude that there is no multicollinearity between the independent variables. Lastly the by looking at the scatterplot of residuals versus predicted values, it seems that no clear pattern can be found, thus homoscedasticity can be assumed (Figure 2).

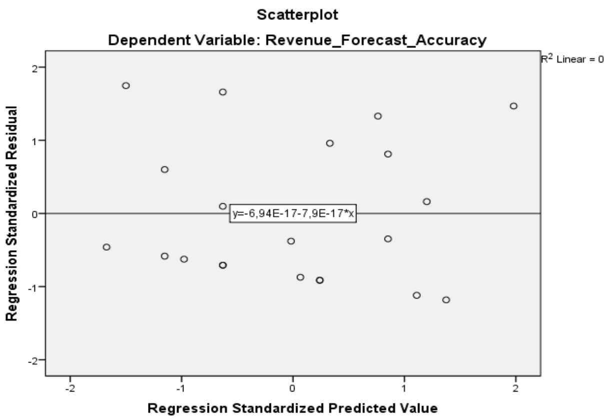

Figure 2: Scatterplot standardized residuals and standardized predicted values

Because not all assumptions for multiple regression analysis were met, and because of the low sample size, a different statistical analysis will be performed to test for dependency between the variables. To be able to perform this test, the variables need to be recoded into dichotomous variables. Industry experience is split up in two categories: inexperience (0-10 year) and experienced (11>). Because of the complexity and variety of nanotechnology a division is made between 10 or less years of experience and more than 10 years of experience. This resulted in 11 participants to be in the "inexperienced" category and 11 participants to be in the "experienced" category. Revenue forecast accuracy is categorized in 0% forecast accuracy (10 participants) and 0%> forecast accuracy (12 participants). Age is categorized in a group younger than 45 (12 participants) and a group with 45 or older (10 participants).

Now that dichotomous variables are created a cross table can be made and a Pierson chi-square can be performed for finding an association. Three different cross tables were created and three different Pearson chi-squares were performed, for each of these the recoded revenue forecast accuracy was located in the column and the recoded industry experience, startup experience and age were located in the rows (Appendices F,G,H). An example of the cross table between startup experience and the recoded revenue forecast accuracy is shown in the table 1

			Revenue Forecast Accuracy		
			0,00	**1,00**	**Total**
Startup Experience	**0,00**	**Count**	9	6	15
		Expected Count	6,8	8,2	15,0
		Percentage within Start-up experience	60,0%	40,0%	100,0%
	1,00	**Count**	1	6	7
		Expected Count	3,2	3,8	7,0
		Percentage within Start-up experience	14,3%	85,7%	100,0%
Total	**Count**		10	12	22
	Expected Count		13,0	9,0	22,0
	Percentage within Start-up experience		45,5%	54,5%	100,0%

Table 1: Cross Table Startup Experience and Recoded Revenue Forecasting Accuracy

With this cross table a Pearson chi-square can be calculated. The Pearson's chi-square is a test to evaluate how likely it is that the observed differences between the count and expected count arose by chance. Because of the small sample size, an alpha of 0.10 will be used. Both with age (0.211) as well as with industry experience (1.000) no significant results were found, startup experience did have a chi-square significance of 0.045 which is significant. Before going further with interpreting the test, the data needs to be checked for the following three assumptions: 1) the type of data needs to be categorial or counts; 2) the samples need to be independent of each other; 3) the expected count needs to be more than 5 in each cell. The first two assumptions are fulfilled in this case, but the last assumption not.

In all of the three cross tables 1 or 2 cells contain an expected count of less than 5, thus Pierson Chi-square cannot be used. When this assumption is not met, a Fisher Exact test need to be performed instead of the Pearson's chi-square test. The Fisher Exact test is an almost similar approach but with more conservative results, thus having significant results less often.

The hypothesis used for the fisher's Exact test are as followed:
H_0: Expected count is equal to observed count
H_1: Expected count is not equal to observed count
$\alpha = 0.10$

In the table 2 the results are shown for the three tests performed. Only for startup experience the results significantly reject the H_0 hypothesis which means that the variables startup experience and revenue forecasting accuracy are not independent of each other. For both industry experience as well as age, no significant evidence was found to reject H_0 which means until proven otherwise, age and industry experience are both independent to revenue forecast accuracy

Independent variable	*Industry experience*	*Startup Experience*	*Age*
Pierson's Chi-square	0.937	0.045	0.211
Fisher's Exact test	1.000	0.074	0.391

Table 2: Results Pearson's Chi-Square and Fisher's Exact test

5. DISCUSSION

Because of the low sample size of this research, it is difficult to give valid conclusions about possible relations / associations between the variables. Via some detours the Fisher's exact test came forward to be the test needed for this dataset. By recoding the variables into dichotomies, the Fisher's Exact test could be performed. No significant evidence was found for dependence between industry experience/age and revenue forecast accuracy. This could be because of the heterogeneity and variation of forecasting which makes it too complicated to make use of knowledge gained from experience (Bonner and Lewis, 1990; Clement et al., 2007; Jacob et al., 1999). But these insignificant results could also be because the small sample size creates larger margins of error and a few extreme values can really influence the results. Although my findings oppose those of Cassar when it comes do dependency between industry startup and forecasting performance, my findings are limited by the sample size.

Where Cassar did not find dependency, the fisher's exact test gave significant evidence for dependency between startup experience and revenue forecast accuracy. Maybe this difference is a result of the argument that entrepreneurs who experienced errors in their judgement before are more aware of the inaccuracy of their knowledge and thus act differently according to it (Corbet, 2005). Startup experience helps gaining knowledge about uncertainties related to starting a business (Delmar and Shane, 2006). It could be that the heterogeneity and variation within the Nanotechnology creates more uncertainty when starting a business than for other startups. Thus making startup experience more important in the Nanotechnology (this research) than for low-tech, mid-tech, or high-tech startups (Cassar's research). Although the test gave significance for this dependency, further research should be done whether and to what extend these variables influence forecast accuracy for venture capital backed organizations in the nanotechnology, but also different industries and technologies.

Besides this, an interesting result of this research is that only 1 of the 22 participants is women, which is also an aspect interesting for further research. Is it because there are not many women within the Nanotechnology? Or is it maybe because women receive venture capital less often? Another result that stood out was that every participant within this Nanonext project had a PhD. This maybe shows how complex the nanotechnology industry is or maybe venture capitalist are only interested to finance entrepreneurs with a PhD. Further research could be done to find possible causes for this remarkable result

As mentioned before, there are some limitations to this research. The lack of time and data available resulted in a sample size which is too low to do regression analysis and to perform a Pearson's chi-square. Future research could focus further on these possible relations / associations between experience and revenue forecast accuracy. More focus could also be given to the differences between different industries within the venture capital backed population.

6. CONTRIBUTIONS

6.1 Theoretical Contribution

This paper is a continuation on the paper "Industry and startup experience on entrepreneur forecast performance in new firms" by Cassar (2014). Cassar made use of the Kauffman fourth follow up survey for his dependent variable. In this survey organizations gave answer to the question: How much do you think your business met your expectations for growth between when the business was started and December 31, 2008?". Possible answers were: 1) exceeded; 2) met; or 3) did not meet. In this paper the forecast accuracy is conceptualized as a percentual comparison between the actual revenue and expected revenue, this in order to receive more precise answers and hopefully reduce bias.

Besides this, similar independent variables are used as Cassar but in this research the focus is on venture capital backed Nanotechnology firms. Cassar already gave evidence of experience improving forecasting accuracy for startups in general, but in this paper the same is researched for venture capital backed new firms. Because receiving venture capital is a disruptive change for startups, making an accurate forecast might be more difficult than for non-venture capital backed startups.

Also by focusing on the Netherlands, this research is contributing to the scarce number of startup researches conducted in the Netherlands. As mentioned by the "Centraal Bureau voor de Statistiek" (Centraal Bureau voor de Statistiek, 2019), the number of new firms started in 2018 in the Netherlands is over 191,000. This in combination with the increasing venture capital market with its importance for startups, makes it increasingly interesting to do research into this topic.

6.2 Practical Contribution

The practical contribution will be for organizations like our host organization Golden Egg Check that make assessments of startup investment opportunities. This paper shows that there is a dependency between startup experience and forecast accuracy for nanotechnology venture capital backed startups. Although further research should be done into this, it seems that having startup experience increases the chance of actually reaching the expected revenue. This is interesting to know for both the Venture Capitalists as well as for Golden Egg Check because more value can be given to industry experience when evaluating an investor pitch. No significance was found for dependency between industry experience and forecasting performance within the Nanotechnology, but this paper does show arguments from the literature why and how this dependency might be there.

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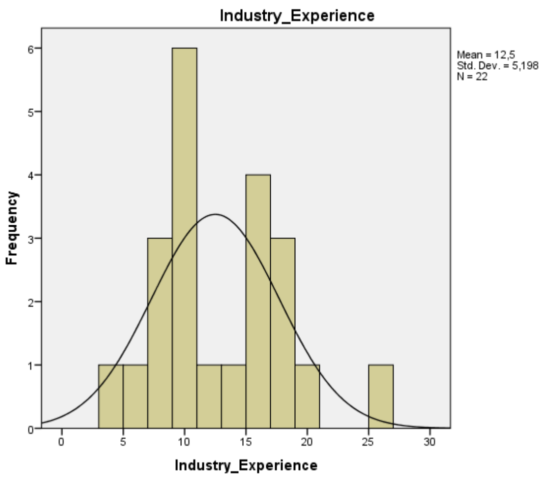
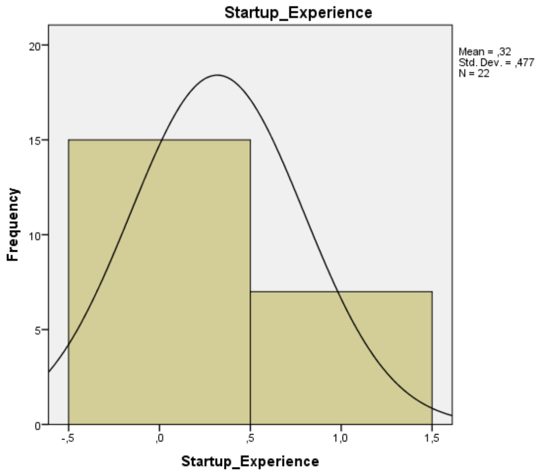
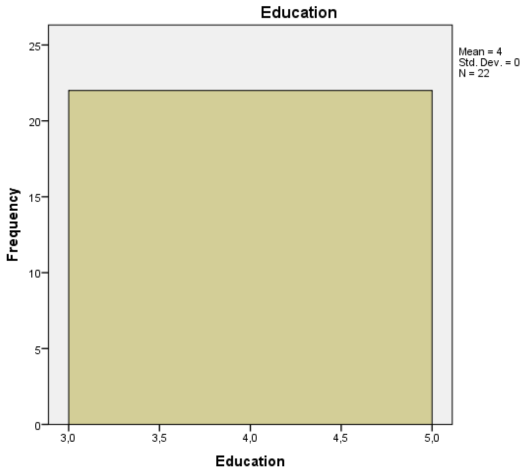
9. APPENDICES

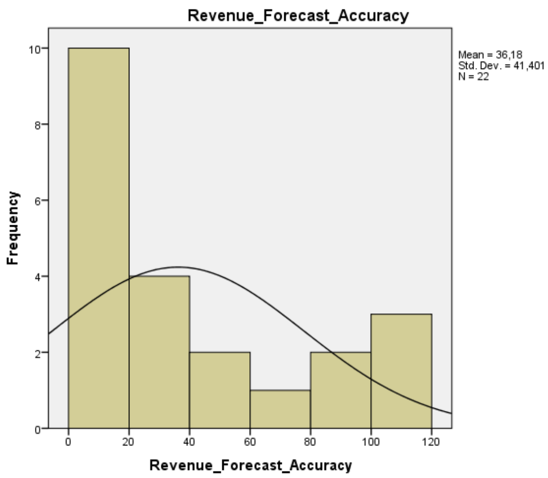
9.1 Appendix A: Frequency Histograms all variables

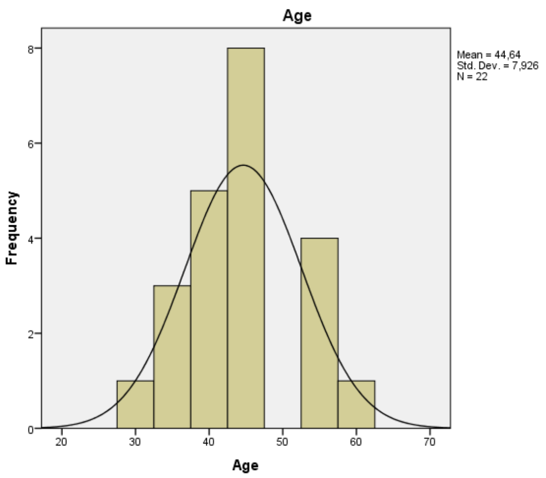


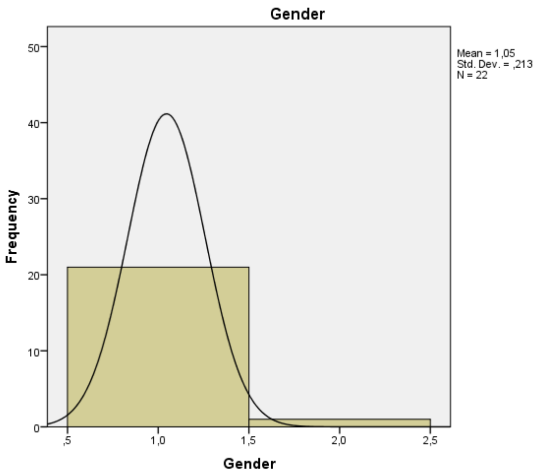




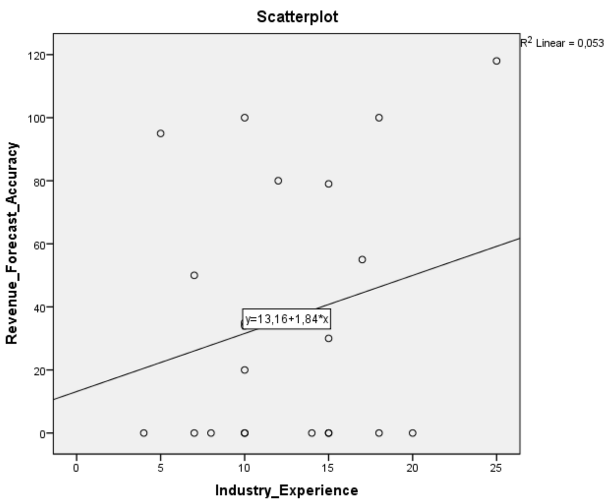
Revenue_Forecast_Accuracy

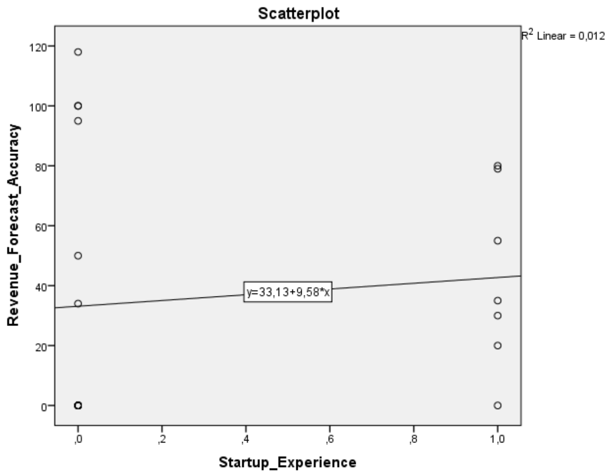




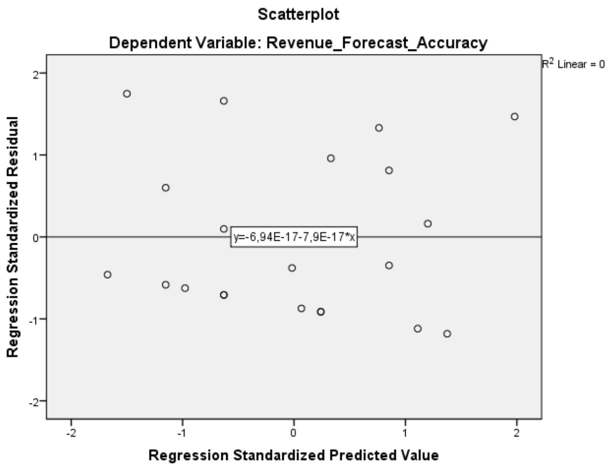


9.2 Appendix B: Scatterplots

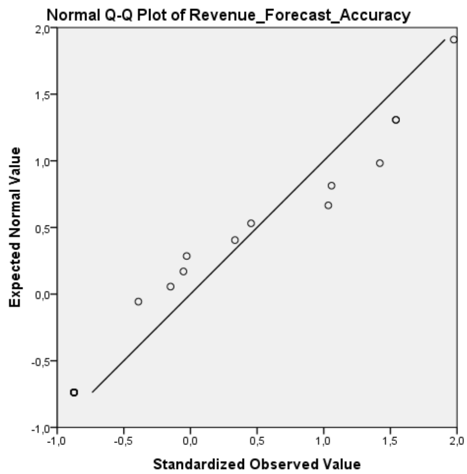


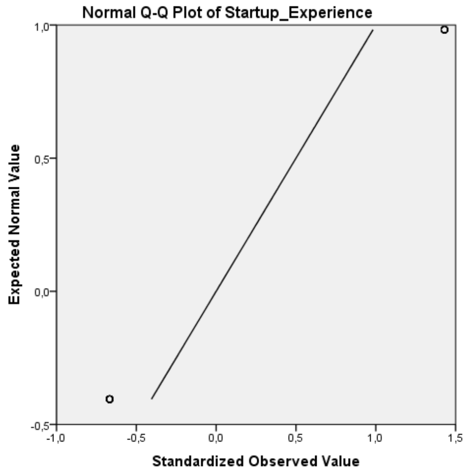


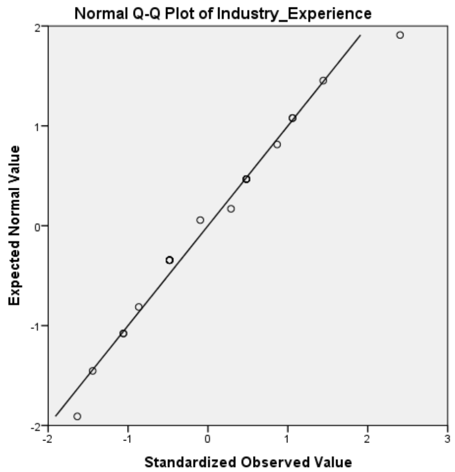
9.3 Appendix C: Scatterplot standerdized predicted values versus standerdized residuals



9.4 Appendix D: Q-Q plots







9.5 Appendix E: Multiconlinarity

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	Startup_Experience	,967	1,034
	Industry_Experience	,967	1,034

a. Dependent Variable: Revenue_Forecast_Accuracy

9.6 Appendix F: Cross table, chi-square and Fisher's test (Startup experience)

			Revenue Forecast Accuracy 0,00	Revenue Forecast Accuracy 1,00	Total
Startup Experience	0,00	Count	9	6	15
		Expected Count	6,8	8,2	15
		Percentage within Start-up experience	60,0%	40,0%	100,0%
	1,00	Count	1	6	7
		Expected Count	3,2	3,8	7
		Percentage within Start-up experience	45,5%	55,5%	100,0%
Total	Count		10	12	22
	Expected Count		10	12	22,0
	Percentage within Start-up experience		45,5%	54,5%	100,0%

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-square	4,023[a]	1	0,045	-	-
Fisher's Exact Test	-	-	-	0,074	0,059

9.7 Appendix G: Cross table, chi-square and Fisher's test (Industry Experience)

			Revenue Forecast Accuracy		
			0,00	1,00	Total
Industry Experience	0,00	Count	5	6	15
		Expected Count	5	6	11
		Percentage within Start-up experience	45,5%	54,5%	100,0%
	1,00	Count	5	6	11
		Expected Count	5	6	7,0
		Percentage within Start-up experience	45,5%	54,5%	100,0%
Total	Count		10	12	22
	Expected Count		10	12	22,0
	Percentage within Start-up experience		45,5%	54,5%	100,0%

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-square	0,000[a]	1	1,000	-	-
Fisher's Exact Test	-	-	-	1,000	0,665

9.8 Appendix H: Cross table, chi-square and Fisher's test (Age)

			Revenue Forecast Accuracy		
			0,00	1,00	Total
Startup Experience	0,00	Count	4	8	15
		Expected Count	5,5	6,5	15
		Percentage within Start-up experience	33,3%	66,7%	100,0%
	1,00	Count	6	4	10
		Expected Count	4,5	5,5	10
		Percentage within Start-up experience	60%	40%	100,0%
Total	Count		10	12	22
	Expected Count		10	12	22,0
	Percentage within Start-up experience		45,5%	54,5%	100,0%

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-square	1,564[a]	1	0,211	-	-
Fisher's Exact Test	-	-	-	0,391	0,206

9.9 Appendix I: Overconfidence

Paper	Relevance	Conclusion
"Determinants of analysists' revenue forecast accuracy" (Lorenz, T., Homburg, C., 2018)	This paper gives insight about the many determinants of revenue forecast accuracy, and finds significant evidence that one of these determinants is forecasting experience	Forecast horizon, forecast frequency, forecast portfolio, reputation, earnings forecast issuance, forecast boldness, analysts' prior performance in revenue forecasting and **analysts' forecasting experience** are all determinants of revenue forecast accuracy.
"Industry and startup experience on entrepreneur forecast performance in new firms" (Cassar, G., 2014)	This paper gives empirical evidence that especially in High tech industries (such as nanotechnology) industrial experience improves overall forecasting performance. This paper is a good basis for my paper only I want to focus on the revenue forecast by venture capital backed startups in the nanotechnology.	He made a theoretical framework in which he empirically investigated the influence of both industry and startup experience on the forecast performance of entrepreneurs. He found significant evidence that, especially in high tech sectors, industry experience does improve forecasting performance. No significant evidence was found for startup experience influencing forecasting performance.
"Determinants of analysts' cash flow forecast accuracy" (Pae, J., Yoon, S., 2012)	Although cash flow forecasting is not the same as revenue forecasting, this paper does show that financial forecasting experience does improve a financial forecast.	Cash flow forecast accuracy can be determined by **cash flow forecasting frequency, cash flow forecasting experience**, number of companies followed, forecast horizon, and past cash flow forecasting performance.
"Analyst characteristics, timing of forecast revisions, and analyst forecasting ability" (Kim, Y., Lobo, G.J., Song, M., 2011)	Another paper that shows that experience reduces forecasting errors and thus improves forecasting performance.	They found that analysts that follow fewer industries, analysts employed by larger brokerage firms and analysts with **more firm-specific and general experience** are negatively related to forecasting errors
"Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?" (Clement, M.B., 1999)	Another paper that gives empirical evidence that experience increases forecasting accuracy	This study finds that analysts' earnings forecast accuracy is positively associated with analysts' experience

9.10 Appendix J: Forecasting Performance

Paper	Relevance	Conclusion
"Forecaster Overconfidence and Market Survey Performance" (Deaves et al., 2019)	This paper shows not only that overconfidence and weak market return forecasting are related, but also that this leads to poor performance	Weak forecasters tend be overconfident in their expectations and provide extreme forecast of market returns, which are thus less likely to be realized. This overconfidence is also leading to poor performance.
"Entrepreneurial overconfidence and firm survival: an analysis using the Kauffman firm survey" (Baek, H.Y., Neymotin, F., 2018)	This paper gives results contrary to most already existing literature by finding evidence that overconfident entrepreneurs have a lower hazard ration (chance of failing) than non-overconfident entrepreneurs. It is relevant to know that not all literature is arguing that overconfidence is bad for an organization's existence	Hazard ratio for overconfident entrepreneurs are lower than those of the non-overconfident entrepreneurs
"Entrepreneurial overconfidence and its impact upon performance" (Invernizzi et al., 2017)	This is one of the papers showing that overconfidence is resulting in firm failure. So factors that influence entrepreneurial overconfidence also indirectly influence the possibility of firm failure.	Overconfidence can be advantageous in the startup phase, but is also related to overoptimistic forecasts resulting in non-optimal outcomes and firm failure.
"Entrepreneurial failure: Statistical and psychological explanation" (Artinger, S., Powell, T.C., 2016)	Espacially in fast emerging markets (such as nanotechnology) "Mistakes are not random but skewed heavily toward excess entry; hence, their decisions are distorted by psychological factors such as overconfidence."	Inexperienced management plays a role in entrepreneurial ventures failing within five years. Besides this, the paper gives empirical evidence that both random errors as well as psychological factors such as overconfidence increase excess market entry, especially in fast emerging markets
"Financial professionals' overconfidence: is it experience, function, or attitude?" (Gloede, O., Menkhoff, L., 2014)	Overconfidence is related to poor forecasting performance. Thus knowing from this paper that experience decreases overconfidence, includes that experience also indirectly improves forecasting performance	This paper shows that working experience is accompanied by less overconfidence.